Carbon prices and forest preservation over time and space in the Brazilian Amazon

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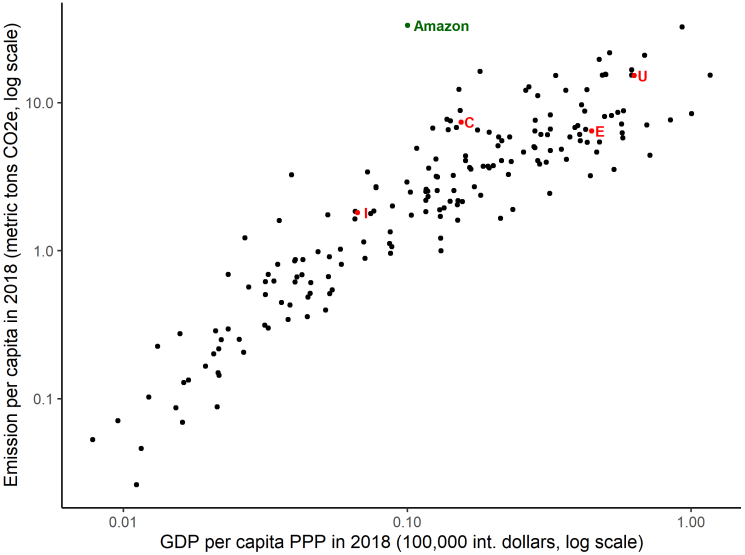
Based on work with Juliano Assunção (Climate Policy Initiative and PUC-Rio), Lars P. Hansen (University of Chicago), and Todd Munson (Argonne National Laboratories)

Motivation

- The Amazon forest contains 123$\pm$23 billion tons of captured carbon that can be released to the atmosphere.(above+below ground)
- Brazilian Amazon occupies 60% of the 2.7 million square miles that comprise the Amazon.
- An area the size of Texas has been deforested in the Brazilian Amazon.
- Portions of Amazon have become a source instead of sink for carbon.

Emissions curve



This research

- Studies the problem of a **fictitious social planner** to provide a benchmark for *ad hoc* policy alternatives
- Analyzes a dynamic model across heterogeneous regions in the Amazon
- Exploits a rich panel data set that covers a cross-section of regions in the Amazon
- Uses numerical methods to achieve a necessary degree of economic and environmental richness to achieve credible results.
- Implements a novel refinement to uncertainty quantification.

Today

1. Present basic model
2. Discuss calibration
3. Present results
4. Parameter ambiguity
   - Computation using Hamiltonian Monte Carlo
5. Interactions across sites.

State and control variables

- Sites are denoted $i = 1, \dots, I$ and the state-vector by (Z, X, P^a).
- $Z = (Z^1, \dots Z^I)$, is the vector of site-specific hectares of land used for agriculture.
- $X = (X^1, \dots, X^I)$ is the vector of site-specific stocks of captured carbon (above ground).
- P^a is an index of cattle prices in Brazil in 2017 USD.
  - 85% of deforested land is used for cattle raising.
- P^e is the social price of emissions
- Control $\dot{Z}$
- State constraints:

$$0 \leq Z_t^i \leq \bar{z}^i,$$

where $\bar{z}^i$ is the maximum area for agriculture in site i.

State dynamics

- Carbon capture dynamics

$$\dot{X}^i = -\gamma^i \max\{\dot{Z}^i, 0\} - \alpha X^i + \alpha\gamma^i \left(\bar{z}^i - Z^i\right)$$

  where $\gamma^i > 0$ and $\alpha > 0$.
  - Does not allow for interactions across sites.
- q state Markov chain with possible values for the agricultural price, $p^a_1, \ldots p^a_q$
- An infinitesimal generator given by $q \times q$ matrix $\mathbb{M} = [m_{\ell,\ell'}]$ with non-negative off-diagonal entries and

$$\sum_{\ell' \neq \ell} m_{\ell\ell'} = -m_{\ell\ell} > 0.$$

Outputs

- Agricultural output

$$A^i = \theta^i P^a Z^i$$

where $\theta^i \geq 0$ is a site specific productivity parameter.

- Net emissions

$$\kappa \sum_{i=1}^{I} Z_t^i - \sum_{i=1}^{I} \dot{X}_t^i$$

where $\kappa > 0$ measures the emissions per hectare of land induced by agriculture.

Quadratic adjustment cost

- Aggregate investment/disinvestment in agriculture over sites

$$\sum_{i=1}^{I} |\dot{Z}^i|$$

- Quadratic costs

$$\frac{\zeta}{2}\left(\sum_{i=1}^{I} |\dot{Z}^i|\right)^2$$

Social planner's objective

- Planner maximizes

$$\int_0^\infty \exp(-\delta t)\mathcal{E}\left(\sum_{i=1}^{I}\left[P^e\left(\dot{X}_t^i - \kappa Z_t^i\right) + P_t^a \theta_i Z_t^i\right] - \frac{\zeta}{2}\left[\sum_{i=1}^{I}\left|\dot{Z}_t^i\right|\right]^2 \mid \mathfrak{F}_0\right) dt$$

- Planner chooses site-specific controls U^i subject to the state evolution equations and the initial states
- P^e, price of emissions, reflects a market for offsets and/or a planner's own valuation.
- Parameter heterogeneity often implies boundary solutions for sites.

Adding parameter uncertainty

- $\varphi^i = (\gamma^i, \theta^i)$, $\boldsymbol{\varphi}$ full $2I$ dim parameter vector.
- $\boldsymbol{\varphi} = \varphi(\boldsymbol{\beta})$, $\dim(\boldsymbol{\beta}) < 2I$.
- π baseline distribution of $\boldsymbol{\beta}$.
- $\boldsymbol{d}$ be the vector of decisions and $f(\boldsymbol{d}, \boldsymbol{\varphi}(\boldsymbol{\beta}))$ for the resulting value given the unknown $\boldsymbol{\beta}$.
- $$\max_{\boldsymbol{d}} \min_{g, \int g d\pi = 1} \int f(\boldsymbol{d}, \boldsymbol{\beta}) g(\boldsymbol{\beta}) d\pi(\boldsymbol{\beta}) + \xi \int \log g(\boldsymbol{\beta}) g(\boldsymbol{\beta}) d\pi(\boldsymbol{\beta})$$
- $\xi > 0$ is penalty parameter.
- minimizing g given by:

$$g_{\boldsymbol{d}}(\beta) = \frac{\exp\left[-\frac{1}{\xi} f(\boldsymbol{d}, \boldsymbol{\beta})\right] \pi(\boldsymbol{\beta})}{\int_{\tilde{\boldsymbol{\beta}}} \exp\left[-\frac{1}{\xi} f(\boldsymbol{d}, \tilde{\boldsymbol{\beta}})\right] d\pi(\tilde{\boldsymbol{\beta}})} \quad (1)$$

Sites and initial states

- Sites:
  - Fine grid of 1887 sites of $\approx$ 67 km $\times$ 67 km. Of these 1043 have at least 3% ot area in the Brazilian Amazon biome. Featured in results today without price uncertainty; solve as a deterministic model
  - Coarser grid of 78 sites (featured in results with agricultural price uncertainty, solve using MPC methods with a Markov process for prices of agricultural output and on results about parameter uncertainty and for comparison, deterministic model): Aggregate 16 sites of fine grid to produce sites of $\approx$ 268km $\times$ 268km.
    - Drop three sites with $<$ 3% in Brazilian Amazon biome.
- Agricultural areas in 2017 (Z_0^i)
  - Source: MapBiomas
- Total land available in 2017 ($\bar{z}^i$)
  - Source: MapBiomas
- $X_0^i = \gamma^i(\bar{z}^i - Z_0^i)$.

Agriculture productivity

- Data on cattle sales and area of agriculture for 500+ municipalities that overlapp the biome from 2017 Agriculture Census.
- Regression on geographical variables yield smoother representation and fills in missing data.
- Missing data and unlikely outliers for municipalities with small agricultural area.
- Calculate θ^i for individual sites by weighted average over municipalities.
- Heterogeneity reflects transportation cost and current technology.
- Agricultural price dynamics from monthly observations of cattle prices in Brazil using the 25% and 75% quantiles to infer two-state transition matrix.
- Adjustment cost parameter, ζ, set so marginal cost of changing land use matches forest to pasture transition cost estimated by Araujo, Costa, and Sant'Anna (2022).
    - Need to explore asymmetry

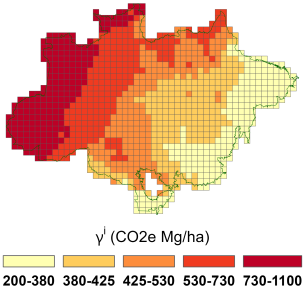
Carbon dynamics I

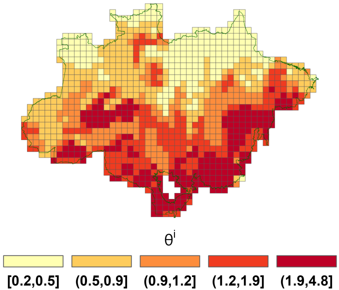
- γ^i: Extract random sample of 1.2M 30m-pixels and select 893,753 pixels that could be considered **primary forest** in 2018 (pixels with no deforestation at least since 1985). Add *a*bove ground biomass density data for 2017, from ESA Biomass (Santoro and Cartus (2021)). Biomass data comes in a grid format ∼100m, so spatially match it to sample and calculate average CO_2 density (Mg/ha).
- Calculate mean γ^i for municipalities.
- Regression on geographical variables yield smoother representation and fills in missing data.
- Calculate site γ^i by weighted average over overlapping municipalities.
- α, carbon depreciation parameter, set so convergence of carbon accumulation process is 100 years. (Henrich et al.(2021)).
- κ calibrated from agricultural net annual emission data at the state level available from SEEG.

Baseline distribution

- Use conjugate prior updating (Hansen and Sargent (2013), Section 5.3) to produce a baseline distribution π of the vector $\boldsymbol{\beta}$ that is used for the case of parameter uncertainty

Site-specific Parameters γ^i and θ^i (1043 sites)





Computational Approach

- Discrete-time (year) approximation
- Deterministic prices (78 or 1043 sites): Interior Point Method: inequalities are approximated with logarithmic penalty functions.
- Uncertain prices (78 sites): Add Model Predictive Control:
  - Finite-horizon approximation with two horizons:
    - Relatively short uncertainty horizon (u.h.) where controls are computed as a function of potential shock realizations (six periods);
    - Longer horizon where the control solutions are approximated by eliminating shocks beyond the uncertainty horizon (200 periods).
  - Solve the model again in subsequent periods with the same u.h..
  - Choose u.h.$=$ 6) because value function changes little from u.h. $= 5$.
  - Interested in first 50 years

Parameter uncertainty

i) Given a g, solve the maximization problem for a candidate $\boldsymbol{d}$. May ignore relative entropy penalty.

ii) For given $\boldsymbol{d}$, solve the minimization problem to obtain new g.

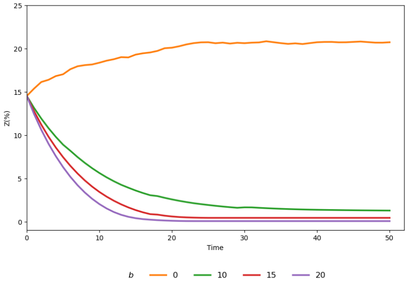
iii) Repeat until achieve convergence.

- For step ii) use quasi-analytical solution (1) and Markov chain Monte Carlo method that is based on Hamiltonian dynamics. and that is often more efficient for high dimensional problems than Metropolis-Hastings (Neal et al. (2011), Carpenter, Gelman, Hoffman, Lee, Goodrich, Betancourt, Brubaker, Guo, Li, and Riddell (2017)).

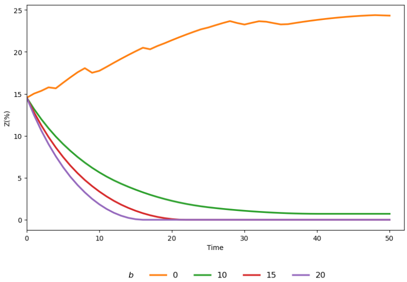
Planner's own valuation - Inferred shadow price of carbon from aggregate behavior 1995-2008

- 1995 - Begin reliable price data. 2008 - Announcement of Amazon Fund that incentivizes preservation of the forest with resources from Norway. (NOK 8.3 billion in 2009-2018)
- Observe prices P_t^a in 95-08 and find P^{ee} that produces $Z_{2008} = Z_{2008}^o$.
- Price P^{ee} that matches observed deforestation varies with model chosen.
- A model where, implicitly, a planner would act more aggressively against preservation would imply a larger P^{ee}.
- Larger P^{ee} applied to future decisions lowers deforestation (increase reforestation).
- $P^e e$ that vary with model brings future trajectories across models closer.
- Similar observation when comparing discount rates.

Evolution of agricultural area (deterministic case, $P^a = P^s$)



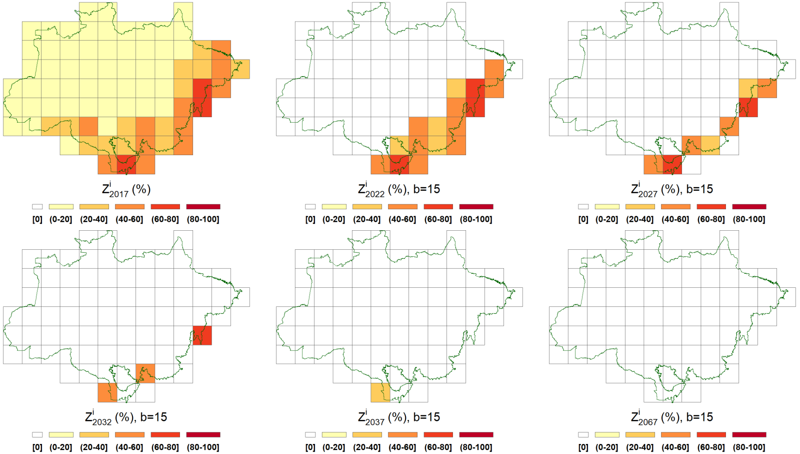
1043 Sites



78 Sites

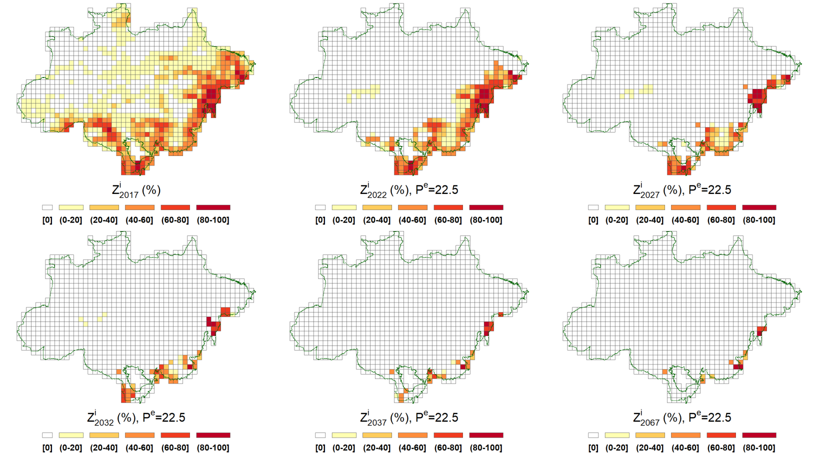
- $P^{ee} = \$7.9$ ($\$7.5$) for 1043 (78) sites
- Business as usual agr. area $\sim 25\%$ - may result on tipping of east, south and central Amazon (Lovejoy and Nobre (2018))

Evolution of occupation by agriculture, 78 sites, $b = 15, P^a = P^s$



- Much of the reallocation in 15 years

Evolution of occupation by agriculture, 1043 sites, $b = 15, P^a = P^s$



- Much of the reallocation in 15 years

Planner Value Decomposition (200 years)

Table: 78 Sites - Deterministic case

P^a (\$)	P^e (\$)	b (\$)	Agricultural Output (\$ 10^{11})	Net Transfers (\$ 10^{11})	Climate Services (\$ 10^{11})	Adjustment Costs (\$ 10^{11})	Planner Value (\$ 10^{11})
42.03	7.5	0	3.86	0.00	-1.57	0.08	2.21
42.03	17.5	10	0.52	1.16	0.87	0.12	2.43
42.03	22.5	15	0.28	1.97	0.98	0.18	3.05
42.03	27.5	20	0.21	2.71	1.01	0.22	3.72
42.03	32.5	25	0.18	3.45	1.03	0.26	4.40
44.76	7.5	0	4.27	0.00	-1.72	0.09	2.47
44.76	17.5	10	0.67	1.08	0.81	0.10	2.46
44.76	22.5	15	0.31	1.95	0.98	0.16	3.07
44.76	27.5	20	0.24	2.70	1.01	0.22	3.74
44.76	32.5	25	0.19	3.44	1.03	0.25	4.42

Notes: For P^a, 42.03 is the stationary price and 44.76 is the high price (75th percentile of the series). Climate services are calculated using baseline shadow price ($b = 0$).

Planner Value Decomposition (200 years)

Table: 1043 Sites - Deterministic case

P^a (\$)	P^e (\$)	b (\$)	Agricultural Output (\$ 10^{11})	Net Transfers (\$ 10^{11})	Climate Services (\$ 10^{11})	Adjustment Costs (\$ 10^{11})	Planner Value (\$ 10^{11})
42.03	7.9	0	3.83	0.00	-1.33	0.07	2.42
42.03	17.9	10	0.66	1.10	0.87	0.11	2.52
42.03	22.9	15	0.39	1.89	0.99	0.17	3.12
42.03	27.9	20	0.25	2.67	1.05	0.21	3.77
42.03	32.9	25	0.21	3.41	1.08	0.26	4.44
44.76	7.9	0	4.38	0.00	-1.60	0.09	2.68
44.76	17.9	10	0.85	1.02	0.80	0.10	2.57
44.76	22.9	15	0.45	1.87	0.98	0.16	3.15
44.76	27.9	20	0.33	2.63	1.03	0.21	3.79
44.76	32.9	25	0.23	3.40	1.07	0.25	4.46

Notes: For P^a, 42.03 is the stationary price and 44.76 is the high price (75th percentile of the series). Climate services are calculated using baseline shadow price ($b = 0$).

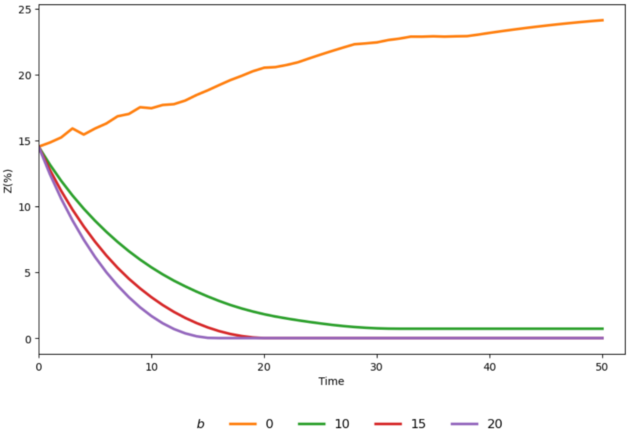
Transfer cost (30 years, 78 sites)

P^a (\$)	P^e (\$)	b (\$)	Net Captured Emissions (billion tons of CO2e)	Net Transfers (\$ 10^{11})	Effective cost (\$ per ton of CO2e)
42.03	7.5	0	-21.12	0.00	NaN
42.03	17.5	10	11.79	1.17	3.58
42.03	22.5	15	13.99	2.09	5.97
42.03	27.5	20	14.66	2.93	8.19
42.03	32.5	25	14.98	3.74	10.37
38.30	7.5	0	-11.05	0.00	NaN
38.30	17.5	10	12.63	1.26	5.33
38.30	22.5	15	14.23	2.13	8.44
38.30	27.5	20	14.75	2.95	11.43
38.30	32.5	25	15.05	3.76	14.41

Notes: For P^a, 42.03 is the stationary price and 38.30 is the low price (25th percentile of the series). 78 sites included.

- Gains from trade
- Even with $P^{a,\ell}$, \$8.44/ton lowers emissions by 25GT $\sim$10% of IPCC budget for 50% chance of $\leq 1.5^\circ C$ from 2023 (250 GT).

Evolution of agricultural area (Uncertainty on P^a)



- P^{ee} =\$7.1

Planner value decomposition (200 years)

Table: 78 Sites - MPC case

P^e (\$)	b (\$)	Agricultural Output (\$ 10^{11})	Net Transfers (\$ 10^{11})	Climate Services (\$ 10^{11})	Adjustment Costs (\$ 10^{11})	Planner Value (\$ 10^{11})
7.1	0	3.67	0.00	-1.45	0.07	2.14
17.1	10	0.48	1.17	0.83	0.12	2.36
22.1	15	0.25	1.98	0.93	0.18	2.99
27.1	20	0.20	2.72	0.96	0.23	3.66
32.1	25	0.17	3.46	0.98	0.27	4.34

Notes: Climate services calculated using baseline shadow price ($b = 0$).

Transfer cost (30 years)

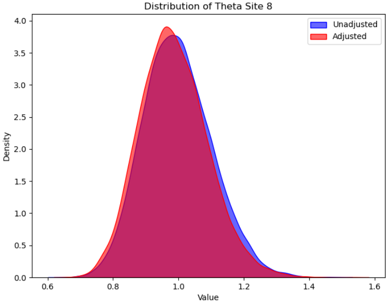
Table: 78 Sites - MPC case

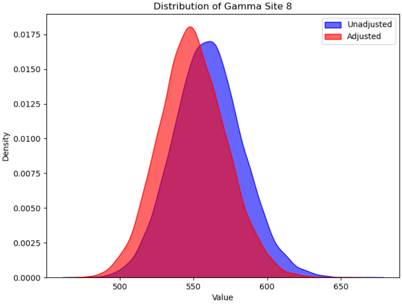
P^e (\$)	b (\$)	Net Captured Emissions (billion tons of CO2e)	Net Transfers (\$ 10^{11})	Effective cost (\$ per ton of CO2e)
7.1	0	-18.94	0.00	NaN
17.1	10	12.18	1.21	3.91
22.1	15	14.14	2.12	6.41
27.1	20	14.71	2.94	8.74
32.1	25	15.02	3.75	11.05

Parameter uncertainty

- Hamiltonian Monte Carlo
- $\xi = 2$
- $P^{ee} = 6.5$

Ambiguity adjustment, $b = 20$, $P^a = P^s$





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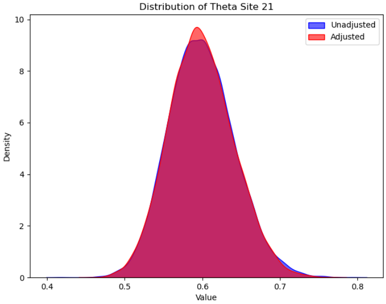
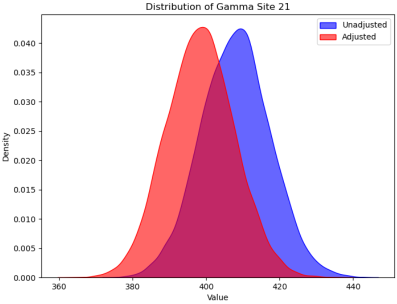
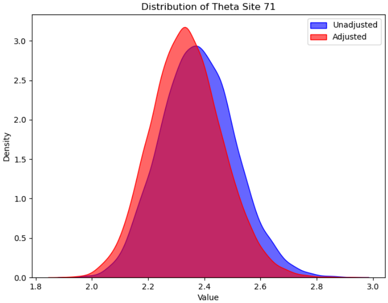
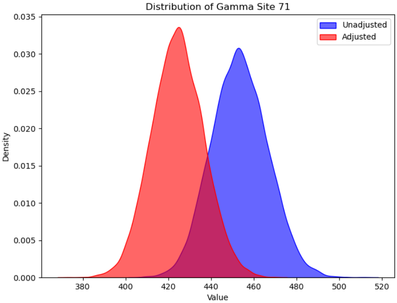


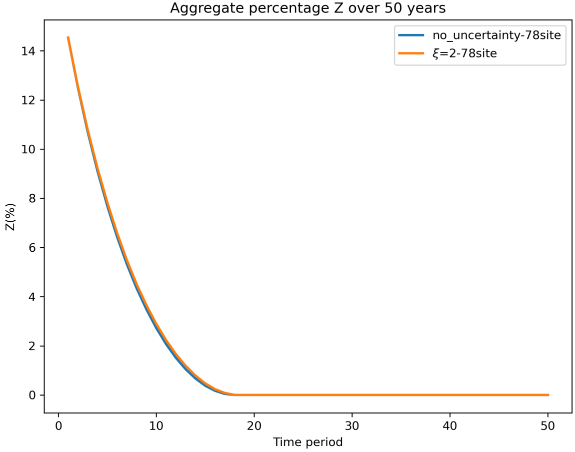


Ambiguity adjustment, $b = 20$, $P^a = P^s$

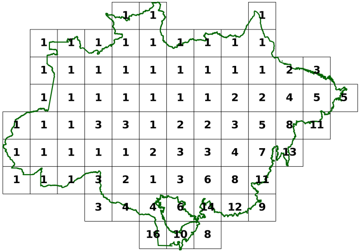




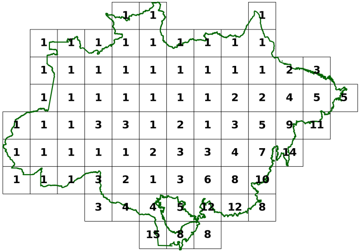
Evolution of agricultural area: productivity ambiguity, $b = 20$, $P^a = P^s$



Year in which reforestation in site i begins ($b = 20$)



ambiguity



no ambiguity

Planner Value Decomposition (200 years)

Table: 78 Sites - HMC case

P^e (\$)	b (\$)	Agricultural Output (\$ 10^{11})	Net Transfers (\$ 10^{11})	Climate Services (\$ 10^{11})	Adjustment Costs (\$ 10^{11})	Planner Value (\$ 10^{11})
6.5	0	3.20	0.00	-1.27	0.06	1.87
16.5	10	0.56	1.07	0.70	0.10	2.24
21.5	15	0.29	1.87	0.81	0.16	2.81
26.5	20	0.23	2.57	0.83	0.21	3.42
31.5	25	0.18	3.28	0.86	0.25	4.07

Notes: $P^a = 42.03$, tghe stationary price. Climate services are calculated using baseline shadow price ($b = 0$).

Transfer cost (30 years)

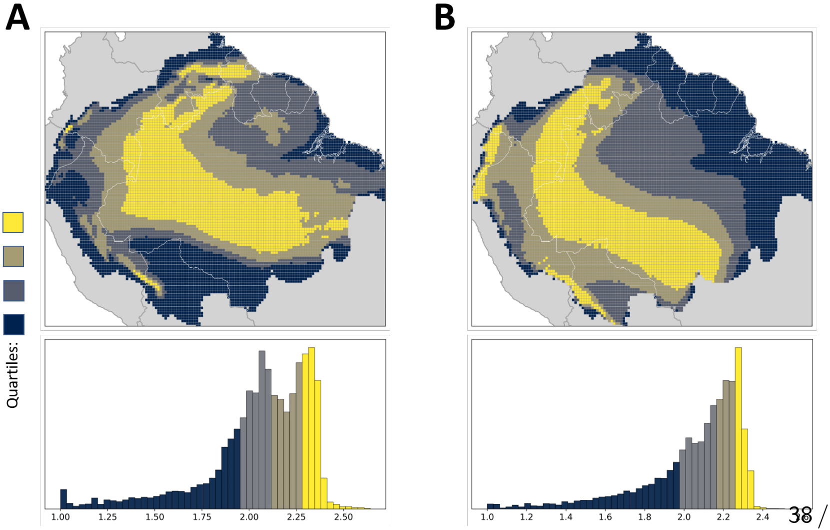
Table: 78 Sites - HMC case

P^e (\$)	b (\$)	Net Captured Emissions (billion tons of CO2e)	Net Transfers (\$ 10^{11})	Effective cost (\$ per ton of CO2e)
6.5	0	-17.73	0.00	NaN
16.5	10	10.85	1.08	3.79
21.5	15	13.20	1.98	6.40
26.5	20	13.85	2.77	8.77
31.5	25	14.22	3.55	11.12

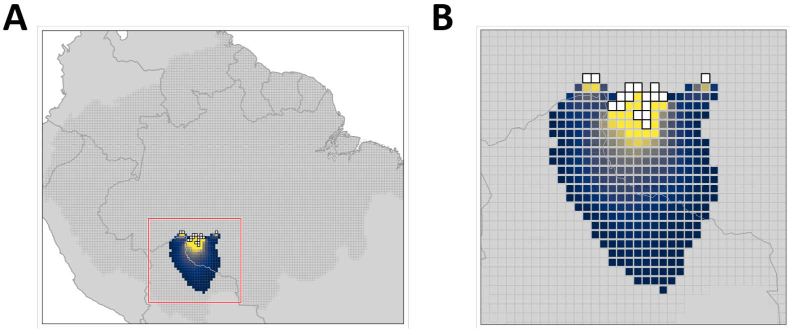
Interactions across sites

- Araujo, Assunção, Hirota, and Scheinkman (2023).
- Amazon produces large fraction of its own rainfall
- Rainfall $\rightarrow$ trees' transpiration $\rightarrow$ recharges atmospheric humidity $\rightarrow$ humidity moves downwind $\rightarrow$ rainfall.
- Less trees $\rightarrow$ less water. Deforestation $\rightarrow$ degradation.
- Mapping transport of water: atmospheric trajectories
- Use variations in back trajectories to estimate impact of upwind Leaf Area Index (LAI) on downwind LAI
- On average, deforestation has a "multiplier" of 2.05.
- Additional externality

Multiplier Effect: **A: total effect of pixels; B: total effect on pixels.**



Transboundary Cascading Effects



- Rondônia: one of the most active frontiers of deforestation
- 17 pixels (25km x 25km) in Rondônia, which are among the highest 5% deforested pixels in the biome.
- Deforestation causes degradation as far as Bolivia
- Deforestation multiplier of 1.87.

Conclusions

- Posed explicit dynamic model across heterogeneous regions in Amazon to assess potential adverse impact of deforestation.
- Rich panel data set
- Computational challenge because the heterogeneity of subregions requires large number of state variables and state-constraints that bind at optimum.
    - Parameter uncertainty
- With modest prices for CO2e, Brazilian Amazon would produce noticiable CO_2 capture.
    - Compared to IPCC budget
    - Compared to Griscom, Adams, Ellis, Houghton, Lomax, Miteva, Schlesinger, Shoch, Siikamäki, Smith, et al. (2017) that identify and quantify "natural climate solutions" (NCS).
- Interactions across sites make predicted path under "business as usual" even more perilous.

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